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Using Artificial Neural Networks to Predict Climate in a Greenhouse

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1. Introduction, Knowledge, Objectives

The aim of this research is to implement and test a model for greenhouse climate by means of Artificial Neural Networks (ANN). ANN are mathematical models of neurons which have proved to be useful in a wide range of modeling applications, including greenhouse climate models (Seginer, 1997; Boaventura-Cunha, 2003). For an overview on ANN and their biological significance, see Kuriscak et al. (2015).
A wide set of data, including as many different conditions in the greenhouse as possible, is an important requisite for building ANN models, due to their poor extrapolation capabilities. Ignoring this could produce a model which is not able to correctly predict values from a different season in the year or when the control strategy is changed (Linker and Seginer, 2004). Even though the literature reports this as an active research field, most of the available models are built and validated with data from short periods of time, instead of complete cultivation periods (He, 2007; Boussab, 2007). Linker and Seginer (2004) suggest to include previous knowledge to improve the performance of ANN. This can be done if a physical model is combined with an artificial intelligence method. Guzmán-Cruz et al. (2009) used data from a whole year in a similar approach, where coefficients of a dynamic model were set using different evolutionary algorithms.
We tested an ANN-based model trained with a big amount of measured data (4 one-year cultivation periods from 2 facilities). Unlike most models reported in the literature, this work uses theoretical solar coordinates as inputs, instead of weather measurements. The aim of this research is to test whether such a simplified model is able to predict the climate inside a tomato greenhouse within minutes-interval. The classical ANN output or one-step prediction (OSP) can be fed back to the system; when done recursively this produces what we have termed long-term predictions (LTP).

2. Material and Methods

The model was trained using data from two similar greenhouses located at the Humboldt University in Berlin, Germany. The two Venlo-Type greenhouses share location, size and construction (6 m wall height, 307 m^2 ground area), being the operation mode their main difference: The *collector* greehouse is equipped with a cooling system and better isolation, allowing it to remain tightly closed longer than the *reference* one.
The data was taken during 4 cultivation periods (2010 through 2013, excluding the winter pauses) of a tomato culture. Both greenhouses are equipped with 6 temperature and relative humidity sensors, whose measurements are averaged and recorded automatically every 5 minutes. Five from those sensors are located at 2 m height and the sixth at 6 m

height. According to the *perfectly stirred tank* assumption (Roy et al. 2002), the average of all 6 sensors is taken as a model input (no spatial gradients are considered).
The data was separated into training, validation and a test datasets, with 272578, 48102 and 58656 records, respectively. Outliers in temperature and relative humidity were replaced by the average of the previous and next value, and the series were low-pass filtered (Savitzky–Golay Filter degree 3, window width 15). The test dataset includes 104 series of 288 adjacent records (each representing a calendar day), evenly distributed over the last cultivation period. The rest of the records was divided into training and validation datasets and randomized. All data records were normalized in the range [-1,1].
The forecasting model was implemented using the FANN 2.2.0 library for C Programming Language (Fast Artificial Neural Networks). The network consisted of a Multilayer Perceptron (MLP) configured as follows:

Inputs (24)

· Internal climatic conditions: air temperature and relative humidity.
· Two actuators: roof ventilation opening and thermal screen closure.
· Four astronomic coordinates: Hour Angle, Solar Declination, Solar Elevation and Theoretical Solar Radiation, which represent a means to code the time (local time and date) in a cyclic way and were calculated according to Torres-Ruiz (2006).

Outputs (2)

· Internal climatic conditions: air temperature and relative humidity.

Three time steps of the 8 input variables ([t,t-1,t-2]) are used to predict the next step (t+1). The number of hidden units was set to 24. The network was trained using the resilient backpropagation (rprop) algorithm.
To build long-term predictions, the simulated values for temperature and relative humidity were fed recursively to the model. The values of the actuators were actual records from the automation system. For each iteration, the solar coordinates were fed according to their respective theoretical values. Each LTP was limited to 6 prediction steps, representing a forecasting of 30 minutes. Fig. 1. shows a simplified block diagram, where the input signals are grouped in three categories for the sake of visual simplicity: C(t) represents the internal climatic conditions (air temperature and relative humidity), M(t) groups the two motor commands (ventilation opening and thermal screen opening), and T(t) includes the four astronomic coordinates. Each iteration takes also the values from the two previous steps as inputs (not shown).

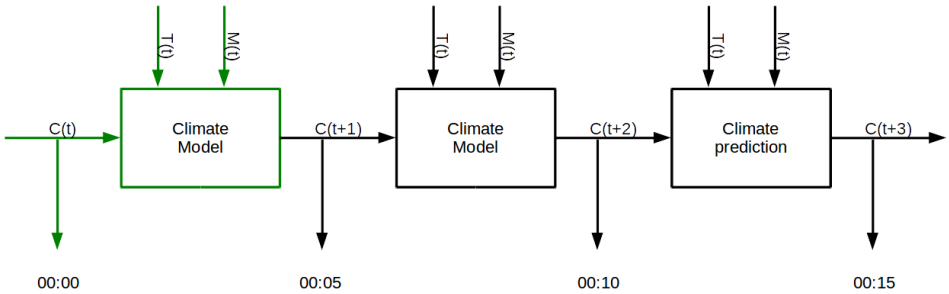

Fig. 1. Generation of LTP by means of recursivity. Only the first iteration takes actual measurements as inputs.

3. Results

After 10000 training epochs, the model reached a Root Mean Squared Error (RMSE) of 0.00877 on the training data, and 0.00894 on the validation data. The trained model was then fed with the test data, producing the results in Table 1. The OSP for both outputs showed a very good fit over the whole validation dataset, being the main issue the presence of comparatively big errors as depicted in Fig. 2. It was found that those deviations coincide with rapid changes in the states of the actuators: both the ventilation and thermal screen can open or close completely within the 5-minutes measuring interval. Since the model takes the input variables in three delay steps, it seems to overreact to those rapid actuator changes. This effect is even more evident when the thermal screen closes. It can be seen at Fig. 2 that the model gives a very good estimation of the relative humidity in those cases where the actuators do not change their state. The temperature OSP behaves similarly, although the overall fit is slightly better (Table 1).

Table 1. Error in climate prediction for the complete test set (58656 simulations).

Predicted steps	Collector Greenhouse				Reference Greenhouse			
	Temperature		Relative Humidity		Temperature		Relative Humidity	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
1	0.1309	0.9986	0.7427	0.9968	0.1054	0.9985	0.6621	0.9978
2	0.2512	0.9949	1.3676	0.9893	0.2024	0.9944	1.3207	0.9912
3	0.4333	0.9850	2.1970	0.9729	0.3550	0.9831	2.2477	0.9751
4	0.6416	0.9682	3.1487	0.9457	0.5372	0.9623	3.3366	0.9468
5	0.8711	0.9439	4.2200	0.9064	0.7546	0.9288	4.5546	0.9048
6	1.1057	0.9140	5.3505	0.8572	0.9838	0.8853	5.8378	0.8512

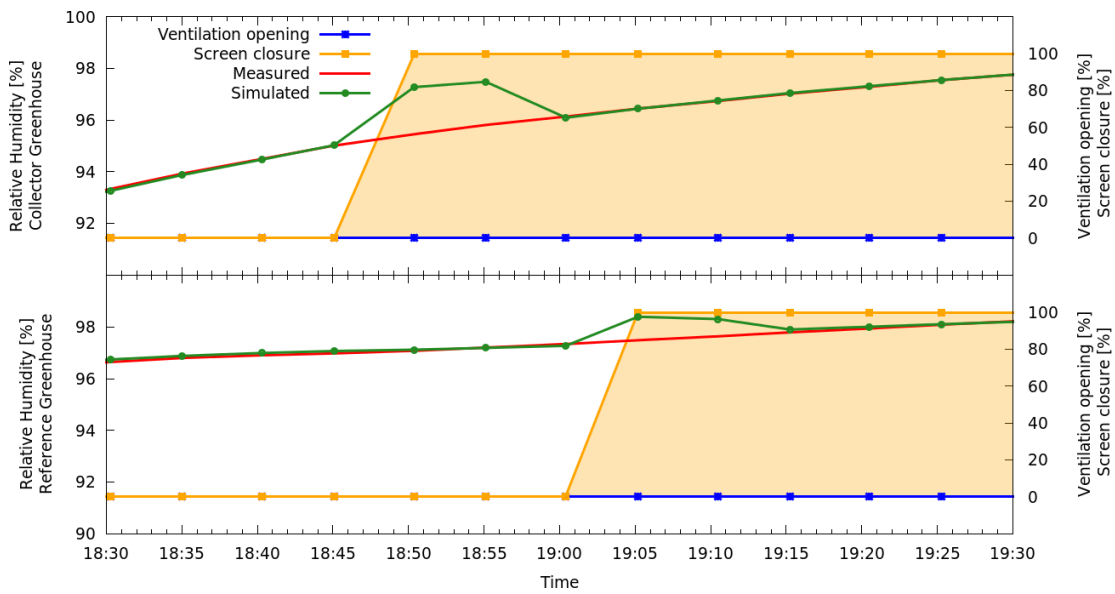

Fig. 2. One-step predictions of relative humidity showing the time in the evening when the thermal screen closes (orange surface). The roof ventilation remained closed in both greenhouses. Values from 17-Apr-2013.

As expected, the generation of LTP led to an increasing error at each iteration step. This can be seen in Fig. 3, where a series of independent LTP simulations are displayed one after the other in a timeline of one day. Once a LTP is triggered, it keeps the same trend. Since each iteration takes the past three values as inputs, in some cases, the predictions shoot up. The temperature LTP had a better fit, but also showed this behaviour. It must be remarked that these deviations in the LTP occured mostly with fast changes in the slope of the simulated variable, regardless of the actuator operation.

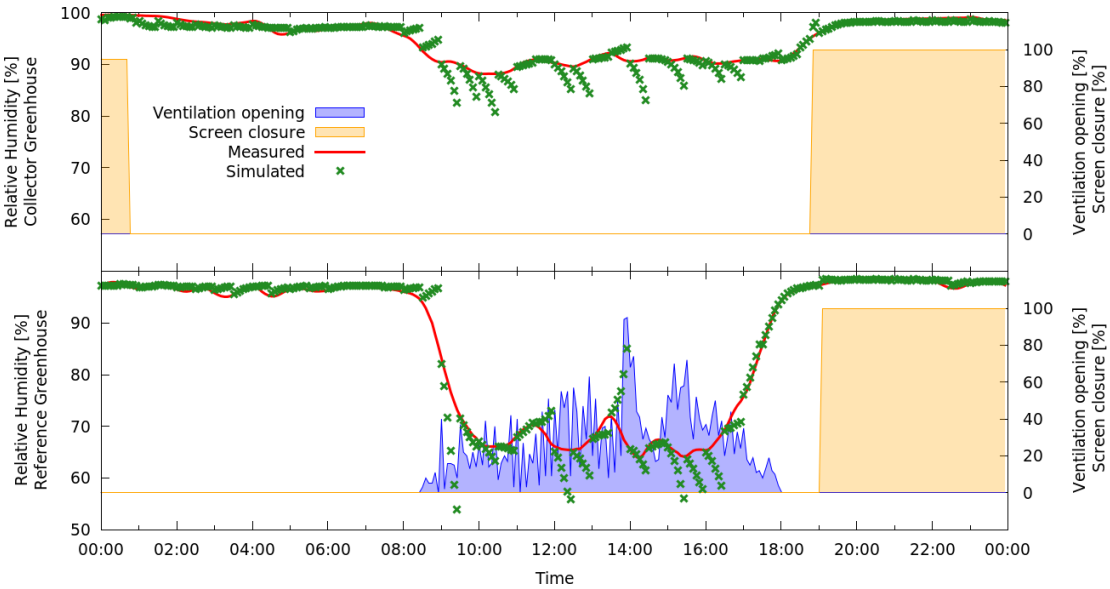

Fig. 3. Relative humidity LTP triggered at 30 minutes intervals. Values from 17-Apr-2013.

4. Discussion

He et al. (2007) modified the training algorithm of an ANN model, achieving a RMSE of 0.8 °C and 1.1 % for predictions of temperature and relative humidity, respectively. They also reported R^2=0.9911 for relative humidity prediction, which might be explained due to the small dataset tested (300 records in 30 minutes intervals). The temperature RMSE they report is similar to that of our model, though our calculation is the result of a recursive LTP and not a 30-minutes-OSP. Our model could reach an RMSE of 1.1 % relative humidity only in the OSP.

Boaventura-Cunha (2003) found that autoregressive prediction models (ARX) perform better than their mechanistic counterparts for predictions up to 60 minutes, which is also consistent with our results, since our recursive approach can be seen as a form of autoregression. The same author points out that ANN are unsuitable for control purposes due to the need of previous offline training. This issue is discussed by Ferreira et al. (2002), who show a comparison of both offline and online training methods for a radial basis function neural networks. They report an absolute error in temperature simulation (t=0) which remained in the range of ±1°C. This is also the case for the OSP and 2-steps-LTP of our model (Table 1). For the error to remain in the range ±1 °C, a RMSE of approximately 0.3 is needed. For the range ±5 % relative humidity, the RMSE should be

around 1.6. Guzmán-Cruz et al. (2009) used a calibrated dynamical model to simulate temperature and relative humidity (t=0) and got correlation coefficients as big as 0.9187 and 0.9332, respectively. The model we present here achieves similar values even after 6 simulation steps of temperature or 5 of relative humidity (Table 1).
To further improve the simulations and deal with the OSP-errors shown in Fig. 2, the actuators signals need to be coded differently. One possibility is to use of principal component analysis to reduce dimensionality, as proposed by He and Ma (2010).

5. Conclusions

The model tested predicted the temperature and relative humidity inside a greenhouse within a range of error similar to, or even better than that reported in the literature. This could be achieved because a big dataset was available for training. These data covers a wide range of practical situations, thus allowing to exclude the weather and plant signals from the model inputs. However, the model needs to deal with two problems to be used for control purposes. One is the overreaction of the OSP to fast (discrete) motor commands. Another one is the presence of strong deviations after several preditcion steps.

6. Literature

Boaventura-Cunha (2003). Greenhouse climate models: An overview, Proceedings of the EFITA Conference: 823-829.
Bussab, M. A.; Bernardo, J. I. and Hirakawa, A. R. (2007). Greenhouse modeling using neural networks, Proc. of the 6th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering and Data Bases: 131-135.
Ferreira, P. M.; Faria, E. A. and Ruano, A. E. (2002). Neural network models in greenhouse air temperature prediction, Neurocomputing 43: 51-75.
Guzmán-Cruz, R.; Castañeda-Miranda, R.; García-Escalante, J. J.; López-Cruz, I. L.; Lara-Herrera, A. and De la Rosa, J. I. (2009). Calibration of a greenhouse climate model using evolutionary algorithms, Biosystems engineering 104: 135-142.
He, F. and Ma, C. (2010). Modeling greenhouse air humidity by means of artificial neural network and principal component analysis, Computers and Electronics in Agriculture 71: S19-S23.
He, F.; Ma, C.; Zhang, J. and Chen, Y. (2007). Greenhouse Air Temperature and Humidity Prediction Based on Improved BP Neural Network and Genetic Algorithm. In: (Ed.), Advances in Neural Networks--ISNN 2007, Springer.
Kuriscak, E.; Marsalek, P.; Stroffek, J. and Toth, P. G. (2015). Biological context of Hebb learning in artificial neural networks, a review, Neurocomputing 152: 27-35.
Linker, R. and Seginer, I. (2004). Greenhouse temperature modeling: a comparison between sigmoid neural networks and hybrid models, Mathematics and computers in simulation 65: 19-29.
Roy, J. C.; Boulard, T.; Kittas, C. and Wang, S. (2002). Convective and Ventilation Transfers in Greenhouses, Part 1: the Greenhouse considered as a Perfectly Stirred Tank, Biosystems Engineering 83: 1-20.
Seginer, I. (1997). Some artificial neural network applications to greenhouse environmental control, Computers and Electronics in Agriculture 18: 167-186.
Torres-Ruiz, E., 2006. Agrometeorología. México: Editorial Trillas. 154p.